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Performance Analysis of Muscular Paralysis Disease using Machine Learning

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Abstract: Electromyography has been used for many years in regulating paralyzed power limb. Captured and Processed EMG is an indication of human movements. EMG signal (called as Mayo signal) will be captured by various wireless sensor of low power, Bluetooth, and small interference. In this paper, the combined time and frequency analysis has been carried out to extract the required features using Wavelet Transform tools using. Further The classification has been carried by 2 different Machine Learning based algorithms i.e., Random Forest (RF), and multilayer perceptron (MLP). The standard data set has been used for the purpose. The classifier model has used 80% data as a training set and the remaining 20% of data as the test set. The result shows that Random Forest and MLP perform better with an accuracy of 98 %. Keeping this valid result with the desired accuracy, this classification model serves as a promising candidate for control of lower limb for paralyzed person.

Keywords: Electromyography, Wavelet transform, Random Forest, Multilayer Perceptron, Mayo signal.

I. INTRODUCTION

Electromyography (EMG) alternatively called as myoelectric activity is the study ofmuscular abnormalities such as muscular dystrophy, inflammation of muscle, peripheral nerve damages. With the advances in technologies a more accurate EMG signal can be captured, with the usage of proper interfaces. EMG signal is measure of electrical currents generated due to muscle fibers dynamics and can be captured at the surface of the skin. EMG signal is a complicated signal controlled by the complex nervous system, and noise is acquired while travelling through different tissues [1]. EMG could be captured by two popular mechanisms either through invasive or noninvasive. [2] EMG provides valuable information about muscular contraction.

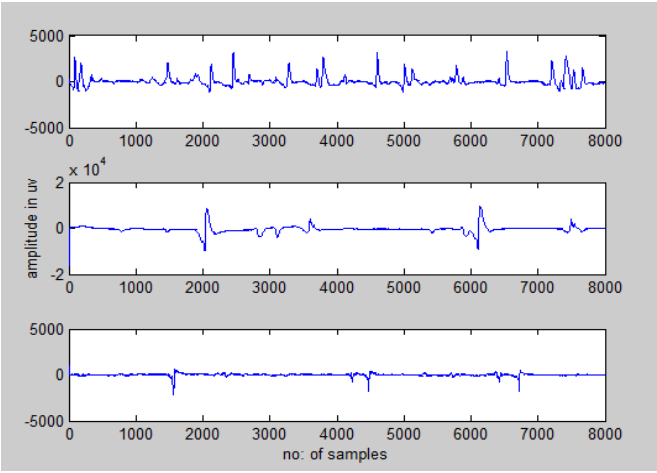

Figure 1: Patterns of normal, ALS and myopathy

The anatomical and physiological characteristics of the muscles make the EMG signalproperties complicated. The EMG signal analysis finds its application in various fields of study such as rehabilitation, ergonomics, and sport science. Feature extraction is very essential mechanism used to extract the useful information from the captured EMG signal.The raw EMG signal has inherently a Time domain representation, but Signal processing application demands additional information, which is missing in the time domain representation, hence EMG signals are generally handled in frequency domain rather than time domain. Further, features are extracted from the captured EMG for predicting the muscular contraction.

The recorded EMG pattern with invasive type approach has peak to peak amplitude 0 to 10 milli volts and frequency ranges from 0 to 500Hz shown in figure 1 depicts the pattern for three classes: normal, ALS, myopathy. The EMG pattern is an indicates the specific neurological disorders; Amyotrophic lateral sclerosis (ALS) leads to death of motor neurons; Myopathy is a muscular disorder leads to muscular weakness. To get better performance of the classification form recorded EMG signal which is a non-stationary signal an appropriate feature extraction scheme should be used.

The objective of the proposed model is to collect EMG data of normal, and paralyzed subjects from experimentation / standard database for various musculoskeletal activities, such as sitting, standing, and gait. Also, analyze the EMG signals in normal,and paralyzed subjects by time domain, frequency domain and time-frequency domain techniques and extraction of important features. And to develop

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classification model based on the features extracted from EMG to classify the data / signal into normal and paralyzed.

The rest of the paper is organized as follows: Section 2 explained the literature of existing models, section 3 describes the proposed model, section 4 deals with result and discussion, section 5 concludes the work.

II. RELATED WORK

Mahaphonchaikul et al., [1] developed a multi-channel electromyogram system using programmable system on chip microcontroller to obtain the surface of EMG signal. Various levels of Daubechies Wavelet family were adopted to extract and analyze the EMG signal. The response of root means square feature extraction method performed better in its accuracy. Farzaneh et al., [2] considered Wavelet Transform to extract Surface EMG (SEMG) features due to its characteristics such as consistent of EMG as a nonstationary signal. In addition, RES index and scatter plot are adopted to check the efficiency. The SEMG features using Daubechies family (db2) yielded best response. Besides prosthetic device control and neuromuscular disease identification, electromyography (EMG) signals can also be applied in the field of human computer interaction (HCI) system. This article represents the classification of (EMG) signal for the detection of different predefined hand motions (left, right, up, and down) using artificial neural network (ANN).

Elamvazuthi et al., [3] investigated the multi-level Daubechies wavelet reconstruction parameters processed using MAV technique. RES index statistical measurement was considered to evaluate the class reparability of the features. Ibrahimy et al., [4] used neural network having backpropagation type, trained by Levenberg-Marquardt training algorithm. The EMG signals have been pre-processed for extracting some features. The frequency-based features are extracted and normalized. A chih Tsai et al., [5] extracted STFT feature to deter-mine multichannel EMG signals. The performance of the novel feature and conventional features for motion pattern recognition using EMG signals. Experiments were made by using an exoskeleton robotic arm generating EMG signals of designated motion patterns.

Abdulhamit Subasi et al., [6] presented bagging ensemble classifier for automated classification of EMG signals. It is assessed to diagnosis of neuromuscular disorders using EMG signals. DWT is used to extract the significant features followed by obtaining the statistical values of DWT. Finally, feature set is used as an input to a Bagging ensemble classifier for the diagnosis of neuromuscular disorders.

Anju Krishna V and Paul Thomas [7] developed disease classification model of EMG signal where spectral features extracted from MUAP. The MUAPs are extracted from the EMG signal. Then, DWT and direct methods are used to obtain spectral features. Finally, KNN classifier is used to classify the features. clinical dataset and samples are used to evaluate the model. Ailton and Júnior [8] developed method based on a bank of matched filters for the decomposition of EMG signals which includes a bank of matched filters, a peak detector, a motor unit classifier and an overlapping resolution module. The experimentation was carried using real EMG data.

Xiaomei Ren et al., [9] used MUAPs and assigns single MUAP segments to their corresponding motor units. The waveforms generated by MUAP are found to be superimposed are then resolved using a peel-off approach. The framework was evaluated using synthetic EMG signals and real recordings generated from healthy and stroke participants. P. Geethanjali [10] explained PCA based feature reduction on pattern recognition for different classifier to obtain statistical features as AR coefficients. The features extracted were tested using kNN classifier to classify the set of features obtained.

R. Begg et al., [11] explained the entire procedure for diagnostic systems initializes to preprocess the raw EMG signal and extract features. In turn, it helps in diagnosis of neuromuscular disorders. Features may be in time and frequency domain. A. Subasi [12] described statistical features of DWT have been used to characterize the EMG interference pattern. Based on that feature, it provides highly significant information between healthy, myopathic, and neuropathic subjects. The extracted features are then be used as input data for classifiers such as NNs and SVMs, to detect neuromuscular disorders. Hassoun et al. [13] developed the NNERVE algorithm to computerize the extraction of individual EMG.

Schizas et al.marked out ANN to classify the action potentials of a large group of muscles. Schizas et al. [15] used model and compared classifiers such as K-means, MLP-NN, SOMs. The K-means algorithm was not suitable, but the combination of ANN and genetic-based models produced promising results. Pattichis et al. [16] considered ANN and MUAP signals collected from the biceps brachii muscle. THE MLP network along with K-means clustering and Kohonen's SOM are used in the work. Pattichis and Elia [17] extended SOM, learning vector quantization (LVQ), and statistical methods for explaining the model of EMG and classifying the bio signals.

Pattichis [18] used WT, that provides a linear time-scale representation for describing MUAP morphology. The classifiers such as BP, the RBF, and SOFM are used for the classification. Subasi et al. [19] evaluated the autoregressive model with wavelet neural network to classify EMG signals. Subasi and Kiymik [20] described the EMG decomposition system using time–frequency and ICA. The PSO optimized SVM classifier combined with statistical features extracted from DWT are compared for

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different ML techniques to classify iEMG signals.

The works contributed with the existing system suffers from lack of accuracy due to the traditional approaches for detecting the paralyzed samples. The proposed model based on the transform domain address the issues faced by the existing methods.

III. PROPOSED MODEL

To analyze the paralysis, Myopathy conditions are considered. Myopathy refers to any disease that affects the muscle tissue. Diseases of the muscle result in weakness, inflammation, tetany, spasms, and paralysis. EMG signals are taken from Database of clinical signals. The material consisted of a normal control group, a group of patients with myopathy. The proposed model for prediction of muscular Paralysis is shown in Figure 2.

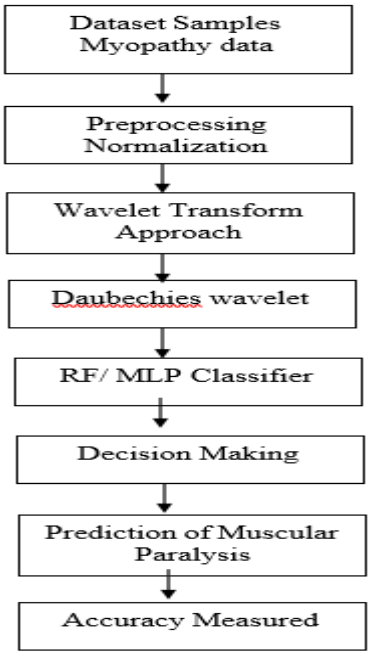

Figure 2: Proposed Model

Myopathy Dataset: The control group consisted of 10 normal subjects aged 21-37 years,4 females and 6 males. 6 out of 10 were in very good physical shape, and the remaining except one were in general good shape. None in the control group had signs or history of neuromuscular disorders. The group with myopathy consisted of 7 patients; 2 females and5 males aged 19-63 years. All 7 had clinical and electrophysiological signs of myopathy.

MUAP analysis

- The EMG signals were recorded under usual conditions for MUAP analysis: Therecordings were made at low (just above threshold) voluntary and constant level of contraction.
- Visual and audio feedback was used to monitor the signal quality.A standard concentric needle electrode was used.
- The EMG signals were recorded from five places in the muscle at three levels ofinsertion (deep, medium, low).
- The high and low pass filters of the EMG amplifier were set at 2 Hz and 10 kHz.

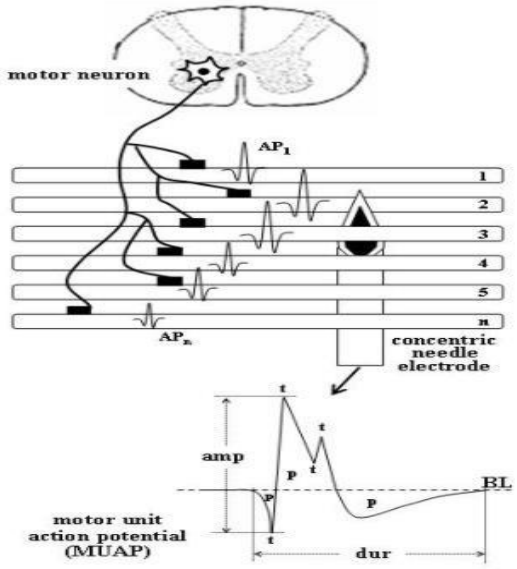

Figure 3: MUAP waveform

The time domain analysis provides the information about the variation in the amplitude ofEMG signal with time. But for most of the biomedical signals the frequency informationis very much essential to understand the nature and characteristics of the signal. The frequency distribution of signal in spectrum will enable in understanding the physiological system in normal and pathological condition.

Wavelet Transform: Since time domain features and frequency domain features in this work gives no significant variations among Myopathy conditions, Wavelet transform (WT) became an effective tool to extract useful information from the EMG signal. A wideclass of literatures has focused on the evaluation and investigation of an optimal feature extraction obtained from wavelet coefficients.

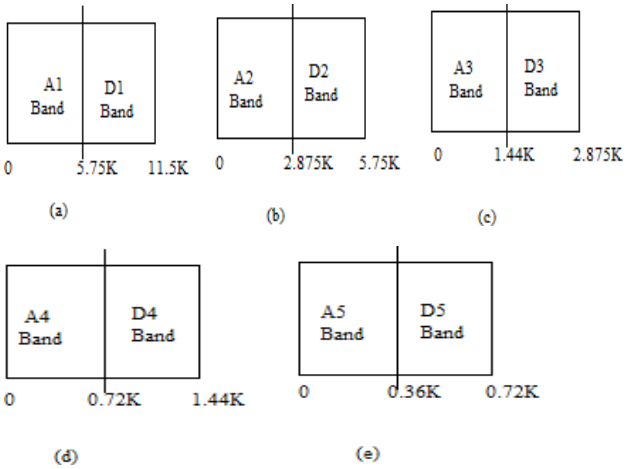

Figure 4: Wavelet Decomposition Levels: (a) A1 & D1 Bands. (b) A2 & D2 Bands.

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(c) A3 & D3 Bands. (d) A4 & D4 Bands. (e) A5 & D5 Bands.

The selection of the Daubechies mother wavelet determines the signal representation. The coefficients derived from wavelet decomposition are too long to be used as features for classification. In this work Wavelet decomposition is achieved for five levels:

Figure 4 shows the Wavelet decomposition for different bands of frequencies. The A1 Band is Approximation Band 1 and D1 is Detail Band 1. Similarly, A2, A3, A4, & A5 are Approximation Bands and D2, D3, D4, & D5 are Detail Bands. The mean value, variance, root mean square, Kurtosis of signal and Skewness of signal features of data samples were extracted to carry out the work.

- Mean Value: The amplitude Mean value of the EMG for selected analysis interval is the most important EMG-calculation, because it is less sensitive to duration differences of analysis intervals. The mean EMG value best describes the gross innervation input of a selected muscle for a given task and works best for comparison analysis.
- Variance: Variance of EMG signal (VAR) is good at measuring the signal power, and it can be expressed as

$$VAR = \frac{1}{L-1}\sum_{i=1}^{L}(x_i)^2$$

- Root Mean Square: Root mean square (RMS) is one of the popular features whichis useful in describing the muscle information. In mathematics, RMS can be calculated using

$$RMS = \sqrt{\frac{1}{L}\sum_{i=1}^{L}(x_i)^2}$$

- Kurtosis: Kurtosis refers to the statistical measure that describes the shape of either tail of a distribution, that is whether the distribution is heavy-tailed (presence of outliers) or light-tailed (paucity of outliers) compared to a normal distribution. In other words, it indicates whether the tail of distribution extends beyond the ±3 standard deviation of the mean or not.

Kurtosis = Fourth Moment / (Second Moment)^2

- Skewness: Skewness is a measure of symmetry in a distribution.

Skewness = (3 * (mean - median)) / standard deviation

In this work, the Data of Myopathy is considered for experimentation. Features are extracted from the Data and are tabulated and represented using chart graphs in section 4.

IV. RESULTS AND DISCUSSION

The Myopathy dataset is used for prediction of muscular paralysis using wavelet transform and Daubechies wavelet mother wavelet technique to carry out the work. After Wavelet decomposition the features are extracted, and results are tabulated. The RF and MLP are used for classification process. The features are extracted for Myopathy Data with wavelet decomposition using Daubechies wavelet of the order 1. The results are tabulated and indicated with chart graphs. The Average values, Maximum values, and Minimum values are A5,D5,D4,D3,D2,& D1 Bands are tabulated, and also indicated using chart graphs.

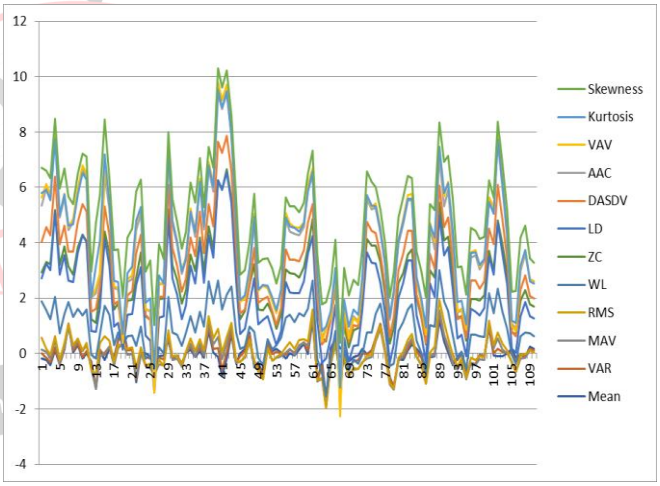

Figure 5: Features extracted for Approximation band A5 with Daubechies wavelet of the order 1for Myopathy Data:

Table 1: Average, Maximum, & Minimum values of features extracted for Approximation bandA5 with Daubechies wavelet of the order 1 for Myopathy Data:

Mean	VAR	MAV	RMS	WL	ZC	LD	DASDV	AAC	VAV	Kurtosis	Skewness	
-0.01533	0.008088	-0.07139	0.128329	0.749999	1.789307	-0.47379	0.94374	0.749999	0.11359	0.053183	0.934849	**Average**
1.227608	0.309414	0.40669	0.587629	1.737406	4.548831	0.018429	1.380933	1.737406	0.402622	1.167766	1.681787	**Maximum**
-1.59089	-0.3242	-0.56988	-0.08637	-0.37997	0.11918	-0.90047	0.152408	-0.37997	-0.24911	-0.28134	0.593849	**Minimum**

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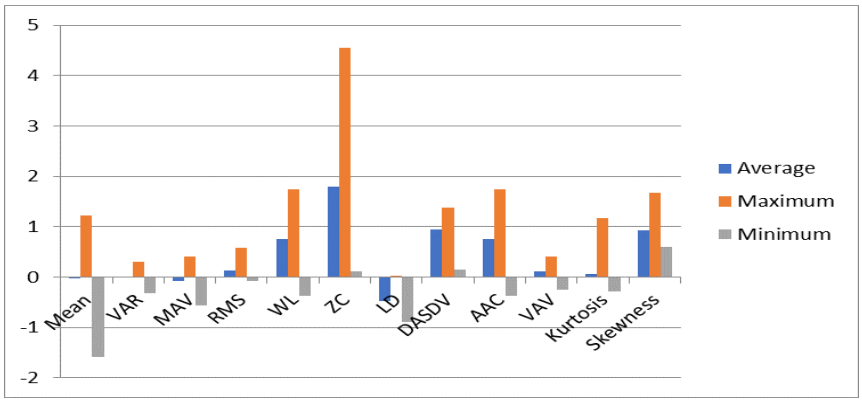

Figure 6: Average, Maximum, & Minimum values of features extracted for Approximation bandA5 with Daubechies wavelet of the order 1 for Myopathy Data

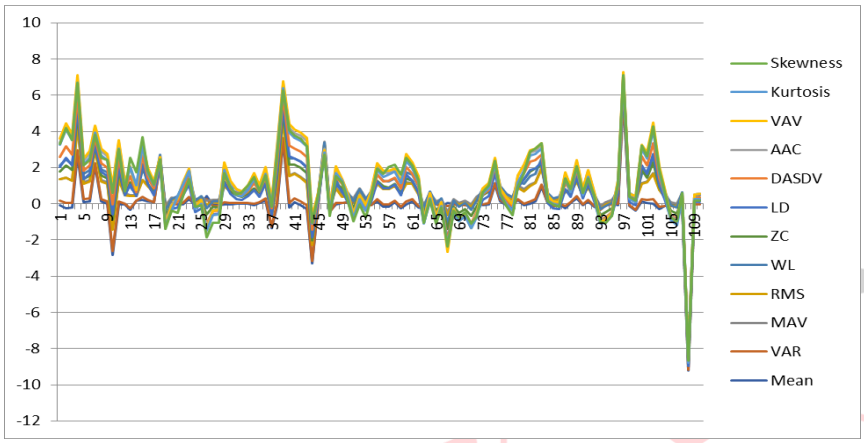

Figure 7: Features extracted for Detail band D5 with Daubechies wavelet of the order 1 forMyopathy Data

Table 2: Average, Maximum, & Minimum values of features extracted for Detail band D5 withDaubechies wavelet of the order 1 for Myopathy Data:

Mean	VAR	MAV	RMS	WL	ZC	LD	DASDV	AAC	VAV	Kurtosis	Skewness	
0.028447	0.059904	0.666265	-0.09584	0.335399	-0.27566	-0.10935	0.319193	0.335399	0.048809	-0.26118	0.01646	Average
5.803884	0.294459	1.508367	0.00552	1.010632	0.267777	0.466111	0.655826	1.010632	0.268946	0.412016	0.712892	Maximum
-9.21394	-0.20102	-0.32172	-0.19007	-0.42092	-0.31828	-0.58523	-0.11729	-0.42092	-0.19573	-0.48165	-0.92782	Minimum

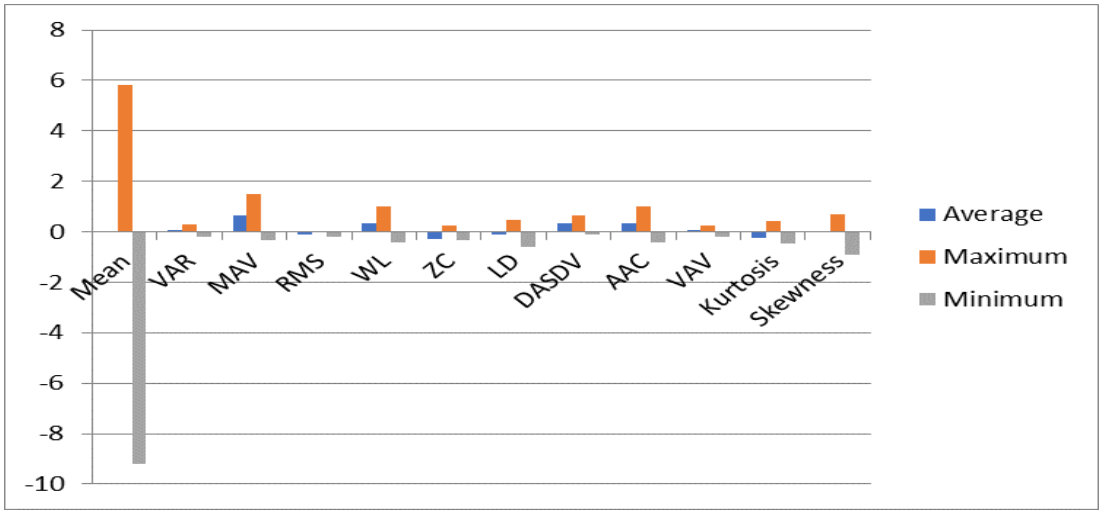

Figure 8: Average, Maximum, & Minimum values of features extracted for Detail band D5 withDaubechies wavelet of the order 1 for Myopathy Data:

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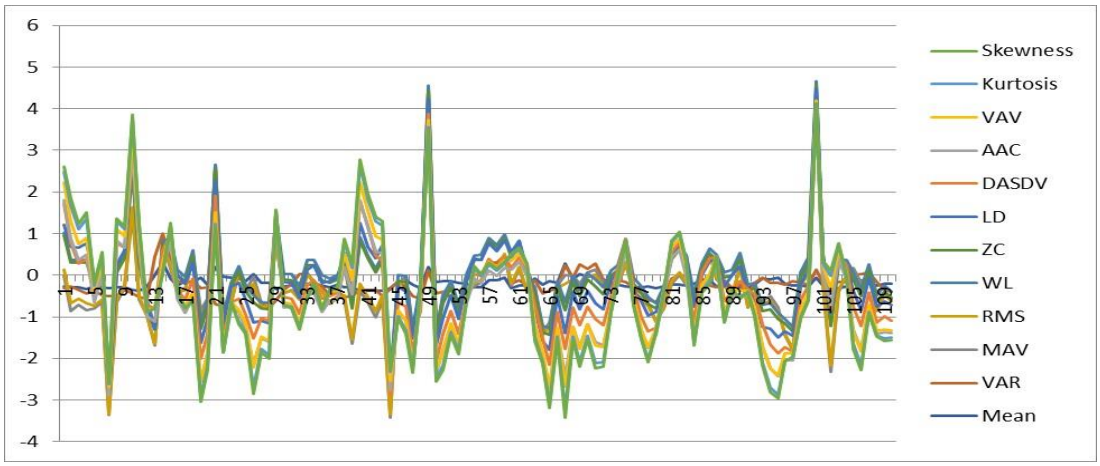

Figure 9: Features extracted for Detail band D4 with Daubechies wavelet of the order 1 forMyopathy Data:

Table 3: Average, Maximum, & Minimum values of features extracted for Detail bandD4 with Daubechies wavelet of the order 1 for Myopathy Data:

Mean	VAR	MAV	RMS	WL	ZC	LD	DASDV	AAC	VAV	Kurtosis	Skewness	
-0.19756	-0.03977	-0.11337	-0.00227	0.403823	-0.12225	-0.06932	-0.20512	-0.25776	0.143654	-0.06932	-0.01065	Average
0.29783	0.706673	4.329367	0.187378	1.125996	-0.04895	0.455153	0.509291	0.159771	0.424911	0.455153	0.164322	Maximum
-0.38421	-0.88312	-3.08545	-0.21046	-0.4366	-0.19933	-0.54782	-0.37369	-0.68	-0.23375	-0.54782	-0.20124	Minimum

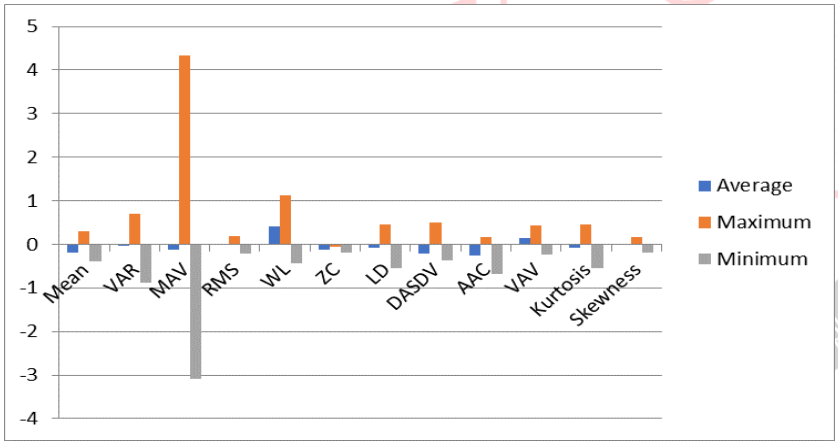

Figure 10: Average, Maximum, & Minimum values of features extracted for Detail band D4 withDaubechies wavelet of the order 1 for Myopathy Data

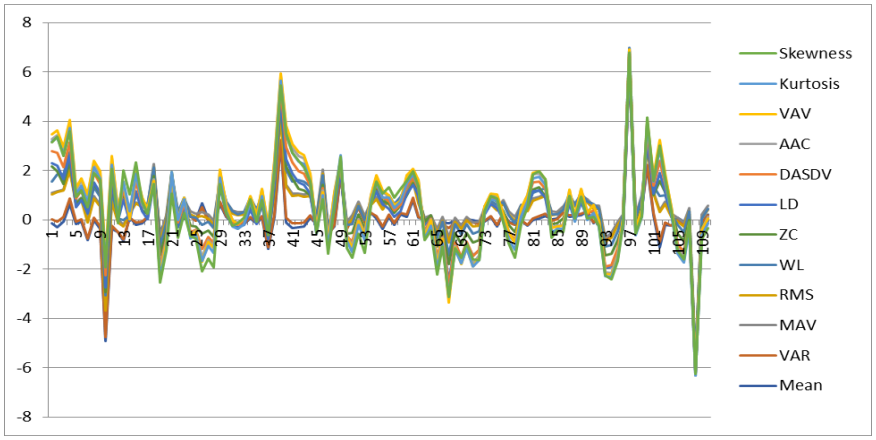

Figure 11: Features extracted for Detail band D3 with Daubechies wavelet of the order 1 forMyopathy Data:

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Table 4: Average, Maximum, & Minimum values of features extracted for Detail bandD3 with Daubechies wavelet of the order 1 for Myopathy Data:

Mean	VAR	MAV	RMS	WL	ZC	LD	DASDV	AAC	VAV	Kurtosis	Skewness	
0.004573	0.023859	0.544894	-0.11365	0.134626	-0.20024	-0.18573	0.232334	0.134626	0.013816	-0.19756	-0.03977	Average
6.238355	0.23198	1.326822	-0.03059	0.724145	1.110509	0.32902	0.53854	0.724145	0.207523	0.29783	0.706673	Maximum
-6.18566	-0.20718	-0.38539	-0.19871	-0.50876	-0.36074	-0.69378	-0.17992	-0.50876	-0.20031	-0.38421	-0.88312	Minimum

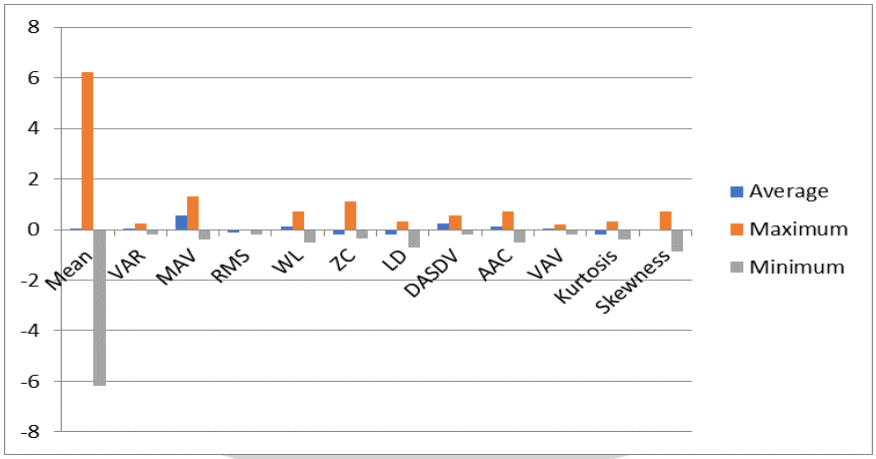

Figure 12: Average, Maximum, & Minimum values of features extracted for Detail band D3 withDaubechies wavelet of the order 1 for Myopathy Data

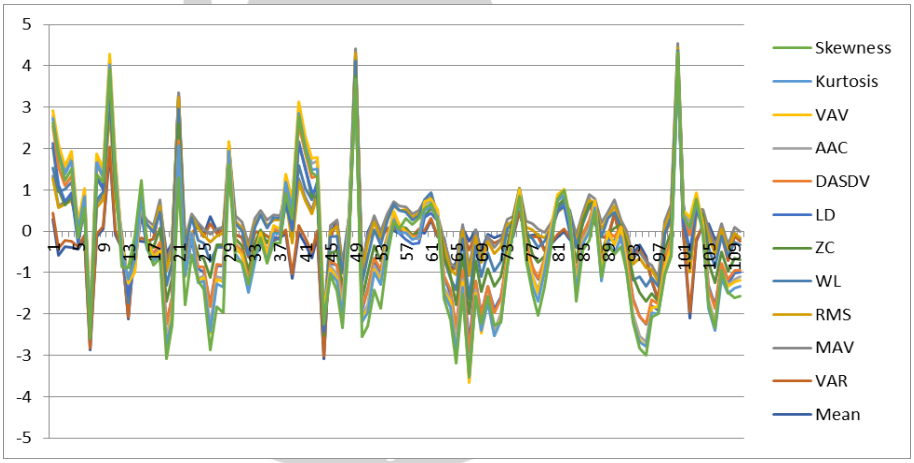

Figure 13: Features extracted for Detail band D2 with Daubechies wavelet of the order 1 forMyopathy Data:

Table 5: Average, Maximum, & Minimum values of features extracted for Detail band D2 withDaubechies wavelet of the order 1 for Myopathy Data:

Mean	VAR	MAV	RMS	WL	ZC	LD	DASDV	AAC	VAV	Kurtosis	Skewness	
-0.11337	-0.00227	0.403823	-0.12225	-0.06932	-0.20512	-0.25776	0.143654	-0.06932	-0.01065	-0.13119	-0.09759	Average
4.329367	0.187378	1.125996	-0.04895	0.455153	0.509291	0.159771	0.424911	0.455153	0.164322	0.290988	0.57643	Maximum
-3.08545	-0.2106	-0.4366	-0.19933	-0.54782	-0.37369	-0.68	-0.23375	-0.54782	-0.20124	-0.27431	-0.7756	Minimum

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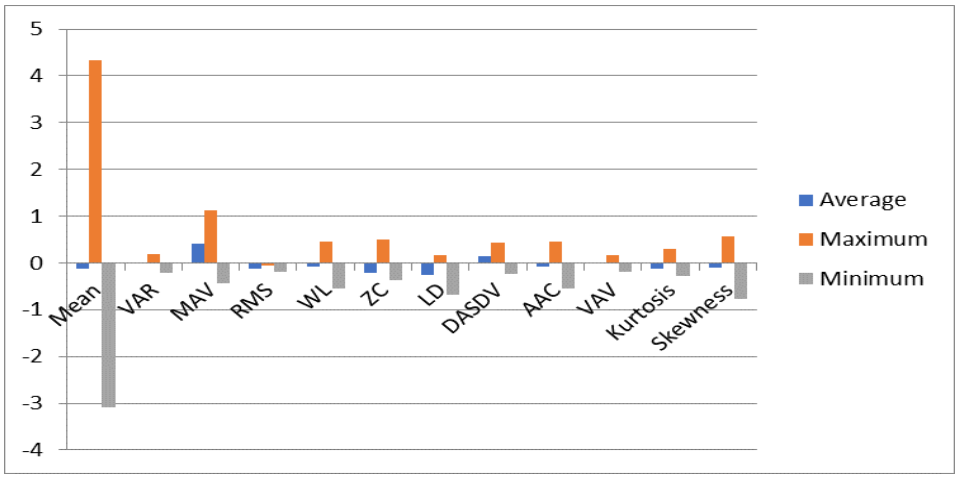

Figure 14: Average, Maximum, & Minimum values of features extracted for Detail band D2 withDaubechies wavelet of the order 1 for Myopathy Data

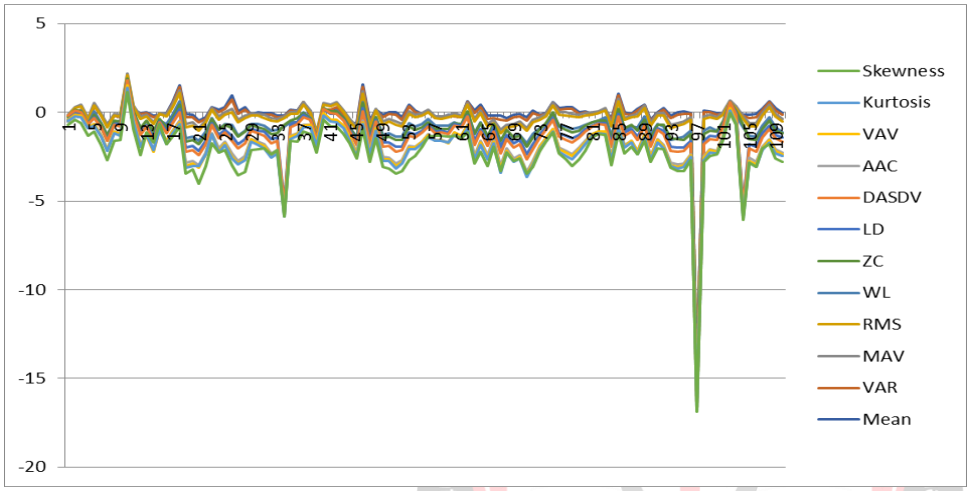

Figure 15: Features extracted for Detail band D1 with Daubechies wavelet of the order 1 forMyopathy Data

Table 6: Average, Maximum, & Minimum values of features extracted for Detail band D1 withDaubechies wavelet of the order 1 for Myopathy Data:

Mean	VAR	MAV	RMS	WL	ZC	DASDV	AAC	VAV	Kurtosis	Skewness	
-0.10391	-0.07043	-0.07326	-0.13484	-0.50177	-0.04317	-0.31844	-0.14304	-0.50177	-0.06398	-0.09895	Average
1.82922	0.087515	0.399253	-0.0645	-0.23916	0.3908	-0.01408	0.210629	-0.23916	0.076545	0.130512	Maximum
-14.7485	-0.24004	-0.57084	-0.19844	-0.72262	-0.18434	-4.46455	-0.36421	-0.72262	-0.21347	-0.16076	Minimum

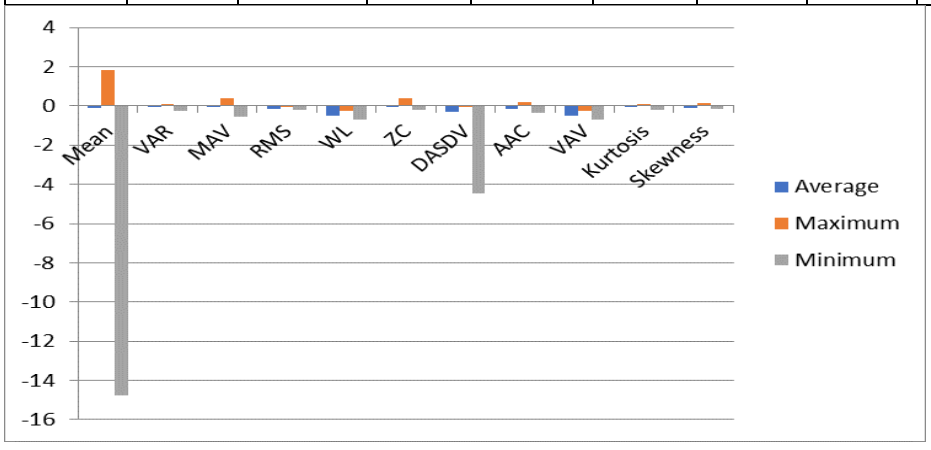

Figure 16: Average, Maximum, & Minimum values of features extracted for Detail band D1 withDaubechies wavelet of the order 1 for Myopathy Data

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Table 7: Average values of features extracted for A5, D5, D4, D3, D2 & D1 Bands withDaubechies wavelet of the order 1 for Myopathy Data:

	Average Values											
	Mean	**VAR**	**MAV**	**RMS**	**WL**	**ZC**	**LD**	**DASDV**	**AAC**	**VAV**	**Kurtosis**	**Skewness**
A5 Band	-0.01533	0.008088	-0.07139	0.128329	0.749999	1.789307	-0.47379	0.94374	0.749999	0.11359	0.053183	0.934849
D5 Band	0.028447	0.059904	0.666265	-0.09584	0.335399	-0.27566	-0.10935	0.319193	0.335399	0.048809	-0.26118	0.01646
D4 Band	-0.19756	-0.03977	-0.11337	-0.00227	0.403823	-0.12225	-0.06932	-0.20512	-0.25776	0.143654	-0.06932	-0.01065
D3 Band	0.004573	0.023859	0.544894	-0.11365	0.134626	-0.20024	-0.18573	0.232334	0.134626	0.013816	-0.19756	-0.03977
D2 Band	-0.11337	-0.00227	0.403823	-0.12225	-0.06932	-0.20512	-0.25776	0.143654	-0.06932	-0.01065	-0.13119	-0.09759
D1 Band	-0.10391	-0.07043	-0.07326	-0.13484	-0.50177	-0.04317	-0.31844	-0.14304	-0.50177	-0.06398	-0.09895	-0.10391

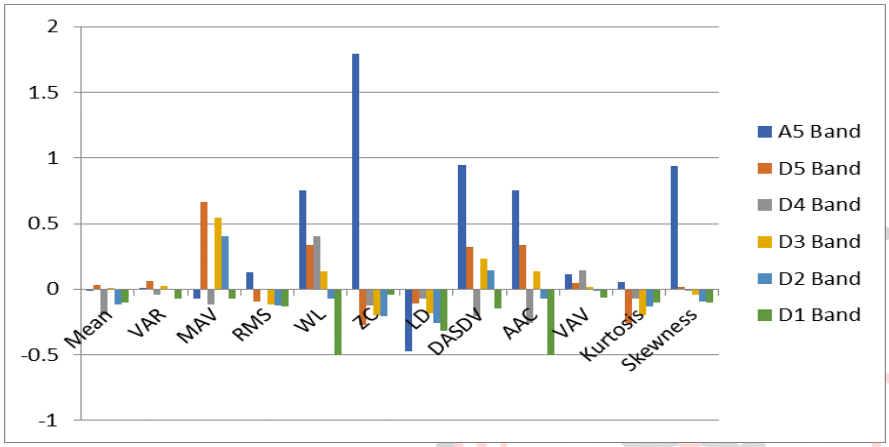

Figure 17: Average values of features extracted for A5, D5, D4, D3, D2, & D1 Bands withDaubechies wavelet of the order 1 for Myopathy Data

Table 8: Maximum values of features extracted for A5, D5, D4, D3, D2 & D1 Bands withDaubechies wavelet of the order 1 for Myopathy Data:

	Maximum Values											
	Mean	**VAR**	**MAV**	**RMS**	**WL**	**ZC**	**LD**	**DASDV**	**AAC**	**VAV**	**Kurtosis**	**Skewness**
A5 Band	1.227608	0.309414	0.40669	0.587629	1.737406	4.548831	0.018429	1.380933	1.737406	0.402622	1.167766	1.681787
D5 Band	5.803884	0.294459	1.508367	0.00552	1.010632	0.267777	0.466111	0.655826	1.010632	0.268946	0.412016	0.712892
D4 Band	0.29783	0.706673	4.329367	0.187378	1.125996	-0.04895	0.455153	0.509291	0.159771	0.424911	0.455153	0.164322
D3 Band	6.238355	0.23198	1.326822	-0.03059	0.724145	1.110509	0.32902	0.53854	0.724145	0.207523	0.29783	0.706673
D2 Band	4.329367	0.187378	1.125996	-0.04895	0.455153	0.509291	0.159771	0.424911	0.455153	0.164322	0.290988	0.57643
D1 Band	1.82922	0.087515	0.399253	-0.0645	-0.23916	0.3908	-0.01408	0.210629	-0.23916	0.076545	0.130512	1.82922

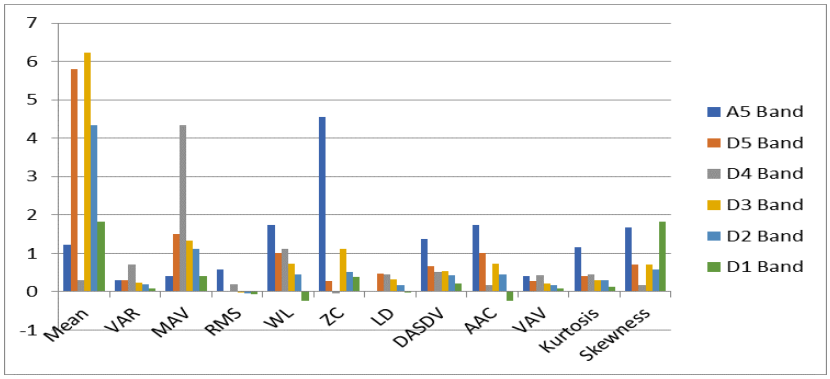

Figure 18: Maximum values of features extracted for A5, D5, D4, D3, D2, & D1 Bands withDaubechies wavelet of the order 1 for Myopathy Data

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Table 9: Minimum values of features extracted for A5, D5, D4, D3, D2, & D1 Bands withDaubechies wavelet of the order 1 for Myopathy Data:

	Minimum Values											
	Mean	**VAR**	**MAV**	**RMS**	**WL**	**ZC**	**LD**	**DASDV**	**AAC**	**VAV**	**Kurtosis**	**Skewness**
A5 Band	-1.59089	-0.3242	0.56988	0.08637	-0.37997	0.11918	-0.90047	0.152408	-0.37997	-0.24911	-0.28134	0.593849
D5 Band	-9.21394	-0.20102	-0.32172	-0.19007	-0.42092	-0.31828	-0.58523	-0.11729	-0.42092	-0.19573	-0.48165	-0.92782
D4 Band	-0.38421	-0.88312	-3.08545	-0.21046	-0.4366	-0.19933	-0.54782	-0.37369	-0.68	-0.23375	-0.54782	-0.20124
D3 Band	-6.18566	-0.20718	-0.38539	-0.19871	-0.50876	-0.36074	-0.69378	-0.17992	-0.50876	-0.20031	-0.38421	-0.88312
D2 Band	-3.08545	-0.21046	-0.4366	-0.19933	-0.54782	-0.37369	-0.68	-0.23375	-0.54782	-0.20124	-0.27431	-0.7756
D1 Band	-14.7485	-0.24004	-0.57084	-0.19844	-0.72262	-0.18434	-4.46455	-0.36421	-0.72262	-0.21347	-0.16076	-14.7485

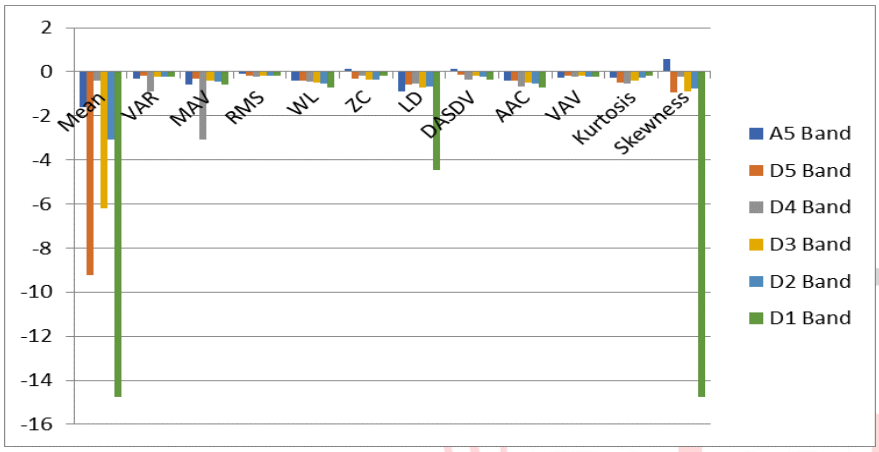

Figure 19: Minimum values of features extracted for A5, D5, D4, D3, D2, & D1 Bands withDaubechies wavelet of the order 1 for Myopathy Data

Overall Observation for Experimentation: The Average value of Mean is increasing between A5-D5 Bands, decreasing between D5-D4 Bands, increasing between D4-D3 Bands, decreasingbetween D3-D2 Bands, and increasing between D2-D1 Bands. The Average value of VAR isincreasing between A5-D5 Bands, decreasing between D5-D4 Bands, increasing between D4-D3Bands, decreasing between D3-D2 Bands, and decreasing between D2-D1 Bands. The Averagevalue of MAV is increasing between A5-D5 Bands, decreasing between D5-D4 Bands, increasingbetween D4-D3 Bands, decreasing between D3-D2 Bands, and decreasing between D2-D1 Bands. The Average value of RMS is decreasing between A5-D5 Bands, increasing between D5-D4Bands, decreasing between D4-D3 Bands, decreasing between D3-D2 Bands, and decreasing between D2-D1 Bands. The Average value of WL is decreasing between A5-D5 Bands, increasingbetween D5-D4 Bands, decreasing between D4-D3 Bands, decreasing between D3-D2 Bands, anddecreasing between D2-D1 Bands. The Average values of ZC is decreasing between A5-D5 Bands,increasing between D5-D4 Bands, decreasing between D4-D3 Bands, decreasing between D3-D2Bands, and increasing between D2-D1 Bands. The Average value of LD is increasing between A5-D5 Bands, increasing between D5-D4 Bands, decreasing between D4-D3 Bands, decreasingbetween D3-D2 Bands, and decreasing between D2-D1 Bands. The Average values of DASDV isdecreasing between A5-D5 Bands, decreasing between D5-D4 Bands, increasing between D4-D3Bands, decreasing between D3-D2 Bands, and decreasing between D2-D1 Bands. The Averagevalues of AAC is decreasing between A5-D5 Bands, decreasing between D5-D4 Bands, increasingbetween D4-D3 Bands, decreasing between D3-D2 Bands, and decreasing between D2-D1 Bands. The Average values of VAV is decreasing between A5-D5 Bands, increasing between D5-D4Bands, decreasing between D4-D3 Bands, decreasing between D3-D2 Bands, and decreasingbetween D2-D1 Bands. The Average value of Kurtosis is decreasing between A5-D5 Bands, increasing between D5-D4 Bands, decreasing between D4-D3 Bands, increasing between D3-D2Bands, and increasing between D2-D1 Bands. The Average value of Skewness is decreasingbetween A5-D5 Bands, decreasing between D5-D4 Bands, decreasing between D4-D3 Bands,decreasing between D3-D2 Bands, and decreasing between D2-D1 Bands.

Random Forest Classifier: A random forest is a meta estimator that fits several decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy.

Multilayer perceptron is a class of feedforward ANN. The term MLP is used ambiguously, sometimes loosely to mean any feedforward ANN.

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Table 10: Response of MLP and RF classifiers for different test sample size

SYM10	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	Seg Lvl	SmplLvl	Seg Lvl	SmplLvl	SegLvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7716	0.7988	0.7787	0.8102	0.8051	0.8142	0.7849	0.8043
RF	0.733	0.7768	0.7351	0.7992	0.7196	0.7431	0.7486	0.826

Table 11: Response of MLP and RF classifiers for different test sample size

SYM9	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	Seg Lvl	SmplLvl	Seg Lvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7829	0.8264	0.763	0.7883	0.7913	0.8415	0.7852	0.826
RF	0.7364	0.7878	0.732	0.7481	0.718	0.7431	0.744	0.8043

Table 12: Response of MLP and RF classifiers for different test sample size

SYM6	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	Seg Lvl	SmplLvl	Seg Lvl	SmplLvl	SegLvl	SmplLvl
MLP	0.7802	0.8044	0.7883	0.8284	0.781	0.8087	0.7847	0.8152
RF	0.7348	0.7741	0.7367	0.781	0.7184	0.754	0.7429	0.7826

Table 13: Response of MLP and RF classifiers for different test sample size

SYM3	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	SegLvl	SmplLvl	Seg Lvl	Smpl Lvl	Seg Lvl	SmplLvl
MLP	0.7884	0.8016	0.7859	0.8211	0.813	0.8469	0.7858	0.7934
RF	0.7326	0.7823	0.735	0.77	0.7196	0.7431	0.7456	0.8043

Table 14: Response of MLP and RF classifiers for different test sample size

SYM2	Test Size = o.4		Test Size = o.3		Test Size = o.2		Test Size = o.1	
	SegLvl	SmplLvl	Seg Lvl	SmplLvl	Seg Lvl	SmplLvl	Seg Lvl	SmplLvl
MLP	0.7933	0.8209	0.7938	0.8284	0.8065	0.8142	0.7893	0.826
RF	0.7557	0.8044	0.7445	0.7956	0.708	0.7322	0.7407	0.8152

The extracted features from the WT and DMW and test features for the different test sizesof myopathy samples are classified using Random Forest and MLP classifiers. The response for the different size samples is tabulated in 10, 11, 12, 13 and 14. Respectively. Based on the results obtained, the accuracy of the model recorded up to 98% and claimed that the results were better compared to the existing model.

V. Conclusion and Future Scope

In this paper, the combined time and frequency analysis has been carried out to extract the required features using Wavelet Transform and Daubechies mother wavelet techniques. The features generated are tested on Myopathy dataset using Random Forest (RF), and multilayer perceptron (MLP) classifiers. The standard data set has been used for the purpose. The classifier model has used 80% data as a training set and the remaining 20% of data as the test set. The result shows that Random Forest and MLP perform better with an accuracy of 98 %. Based on the results obtained, the classification model serves as a promising candidate for control of lower limb for paralyzed person. Further, the modelcan still be improved by considering concatenated or fusion of various spatial and transform domain approaches on various datasets such as ALS, Normal data, real timedata samples to detect the paralyzed data.

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